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EDGE-ENABLED QUANTUM DRONE SENSOR NETWORKS FOR INTELLIGENT URBAN POLLUTION DETECTION

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Abstract

Rapid urbanization has intensified air pollution levels, creating an urgent need for intelligent, real-time monitoring systems that can effectively track and analyze pollutants across dynamic city environments. Conventional Internet of Things (IoT)-based sensing frameworks often face challenges such as latency, limited processing power, and inefficient data management when deployed at large scales. Recent advances in quantum communication and edge artificial intelligence (Edge AI) have opened new avenues for developing highly adaptive and secure environmental monitoring architectures. Despite the proliferation of drone-assisted monitoring systems, most existing models rely on centralized cloud computing, resulting in network bottlenecks and delayed responses. Furthermore, data collected from heterogeneous sensors often lack accuracy due to noise interference and spatial inconsistencies, limiting the reliability of real-time pollution detection and source localization. This study proposes an Edge-Enabled Quantum Drone Sensor Network (Q-DSN) integrated with Convolutional Neural Networks (CNNs) to perform decentralized pollution detection and classification. Quantum key distribution (QKD) enhances communication security among drones, while CNN-based feature extraction processes multispectral data from gas sensors and high-resolution cameras. The edge layer employs a lightweight AI model for on-site prediction, reducing latency and dependence on cloud computation. In addition, an adaptive routing protocol optimizes data transmission between drones and ground stations. Simulation and field-level evaluations demonstrated that the proposed Q-DSN achieved a detection accuracy of 81–84%, a latency reduction to 2.1–2.7 seconds, and an energy efficiency improvement of 20–35% compared to conventional IoT-based and drone-assisted monitoring systems. Communication reliability reached 92% through quantum-secured channels, while edge-level inference enabled real-time classification of pollutants such as CO_2, NO_2, PM2.5, and VOCs across a 2 km² urban testbed.

Keywords:

Quantum Drone Networks, Edge AI, Convolutional Neural Networks, Urban Pollution Detection, Secure Environmental Monitoring

1. INTRODUCTION

Rapid urbanization and industrial expansion have dramatically increased the concentration of airborne pollutants in metropolitan regions, adversely affecting both environmental quality and human health [1]. According to global environmental studies, fine particulate matter (PM2.5), nitrogen dioxide (NO_2), carbon monoxide (CO), and volatile organic compounds (VOCs) are the primary contributors to deteriorating air quality, leading to respiratory and cardiovascular complications among urban populations [2]. To mitigate these risks, the deployment of intelligent monitoring systems capable of real-time pollutant detection and spatial mapping has become essential. Conventional fixed-station monitoring systems, however, suffer from limited spatial coverage and high operational costs, making them insufficient for dynamic urban environments [3].

The combination of drone-based sensor networks with Artificial Intelligence (AI) has emerged as a promising alternative for scalable and flexible air quality monitoring. Drones equipped with multi-sensor arrays can collect data across various altitudes and locations, thereby offering a three-dimensional understanding of pollution dispersion patterns. When combined with Edge AI and Convolutional Neural Networks (CNNs), these platforms can perform real-time analysis and classification of pollutants, significantly enhancing decision-making capabilities for urban environmental management.

Despite their potential, drone-based sensor networks face several technical and operational challenges that hinder their practical deployment. First, the continuous transmission of high-resolution sensor data to centralized cloud servers introduces significant latency and bandwidth overhead [4]. This becomes critical in time-sensitive pollution detection tasks where immediate response is required. Second, ensuring the reliability and security of communication between drones and base stations remains a major concern. Existing wireless networks are vulnerable to interference and unauthorized access, which may compromise the integrity of environmental data [5]. Moreover, data heterogeneity from different sensors often leads to inconsistencies and inaccuracies in pollutant detection, particularly in varying meteorological conditions.

Although existing IoT-based and drone-assisted air quality monitoring frameworks have demonstrated considerable progress, they are often constrained by centralized architectures that limit scalability and computational efficiency. The heavy reliance on cloud processing results in increased latency, reduced energy efficiency, and susceptibility to communication failures during real-time operations [6]. Therefore, there is a pressing need for a decentralized, secure, and intelligent sensing framework that can perform localized processing while maintaining reliable communication and high data fidelity.

The primary objective of this research is to design and implement an Edge-Enabled Quantum Drone Sensor Network (Q-DSN) that combines the advantages of quantum-secure communication, edge computing, and deep learning for efficient urban pollution monitoring. Specifically, the study aims to: develop a CNN-based model for accurate pollutant detection and classification from multispectral and sensor data. Integrate quantum communication protocols, such as Quantum Key Distribution (QKD), to ensure data security and privacy in drone-to-drone and drone-to-ground transmissions. Deploy edge computing mechanisms to enable low-latency inference and energy-efficient data processing. Validate the system's performance through simulation and field-level testing in dynamic urban environments.

The novelty of this work lies in its fusion of quantum communication and Edge AI within drone-based environmental monitoring. Unlike traditional drone networks that depend on cloud-centric processing, the proposed Q-DSN performs localized inference at the edge layer, reducing latency and bandwidth consumption. In addition, the inclusion of quantum-secure data transmission enhances trust and resilience against cyber threats, a feature rarely explored in environmental sensing frameworks. The proposed CNN architecture is optimized for lightweight deployment, ensuring compatibility with energy-constrained drone hardware.

The study introduces a hybrid drone-based architecture that integrates CNN-driven pollutant detection with quantum encryption protocols, enabling real-time, secure, and decentralized air quality assessment.

2. RELATED WORKS

Recent years have witnessed substantial research efforts toward developing intelligent pollution monitoring systems leveraging IoT, drones, and AI-based techniques [6–12]. The convergence of these technologies has enabled high-resolution spatial and temporal pollution mapping, yet several limitations persist in scalability, energy consumption, and communication reliability.

Early IoT-based pollution monitoring systems primarily relied on static sensor nodes integrated with cloud platforms for data storage and analytics [6]. While such systems provided consistent data collection, they suffered from limited spatial mobility and high deployment costs. To overcome these limitations, researchers began employing Unmanned Aerial Vehicles (UAVs) or drones for airborne pollution sensing [7]. These systems facilitated flexible monitoring over large urban areas, offering dynamic adaptability to environmental changes. However, the heavy data transmission between drones and remote servers often led to increased latency and energy consumption.

Machine learning and deep learning models, particularly CNNs and Recurrent Neural Networks (RNNs), have been widely used to enhance pollution prediction accuracy [8]. CNNs excel in processing multispectral and spatial datasets, enabling effective classification of pollutants such as PM2.5 and NO_2. However, most CNN-based systems rely heavily on cloud computation, which introduces significant delays in real-time applications. To address this issue, Edge AI frameworks have been proposed to enable on-site inference, minimizing latency and reducing dependence on centralized infrastructures [9].

Quantum computing and communication have recently gained traction as enablers for secure and efficient environmental monitoring [10]. Quantum Key Distribution (QKD) offers unbreakable encryption for sensor-to-sensor and drone-to-ground communication, ensuring data confidentiality in hostile or congested network environments. Integrating such protocols with Edge AI architectures provides a pathway toward achieving both security and computational efficiency. Nevertheless, few studies have explored this hybridization in environmental sensing scenarios.

Some researchers have focused on developing drone-based multi-sensor fusion frameworks that combine gas sensors, optical cameras, and LiDAR systems for accurate spatial mapping [11]. These multi-modal datasets enhance pollutant identification but introduce new challenges in synchronization and real-time data fusion. Edge computing has been proposed as a viable solution to handle the high data throughput locally, significantly improving system responsiveness.

In recent advancements, edge-assisted UAV networks employing federated or distributed learning have been introduced to support collaborative model training across multiple drones [12]. Such systems reduce the need for data centralization while improving generalization accuracy in diverse urban conditions. However, the security and integrity of communication links remain open research challenges.

3. QUANTUM DRONE SENSOR DEPLOYMENT

The first step in the proposed system involves deploying a network of drones equipped with multi-sensor modules capable of detecting pollutants such as CO_2, NO_2, PM2.5, and VOCs. The drones are strategically positioned across the urban landscape to ensure optimal spatial coverage and minimal sensing overlap. Each drone incorporates a gas sensor array, multispectral camera, and onboard processing unit to perform preliminary data filtering.

The drones are programmed to follow a pre-defined path while dynamically adjusting altitude based on local environmental conditions. This adaptive path planning ensures efficient sampling across vertical and horizontal spatial dimensions. Communication between drones is secured through Quantum Key Distribution (QKD), providing a robust defense against potential cyber threats.

The pollutant concentration estimation at drone i is modeled as:

$$C_i(t) = \sum_{j=1}^{N} w_j \cdot S_{ij}(t) + \epsilon_i(t) \tag{1}$$

where $C_i(t)$ is the estimated concentration at time t, $S_{ij}(t)$ represents the sensor reading from sensor j on drone i, w_j is the weighting factor for sensor accuracy, and $\epsilon_i(t)$ is the measurement noise.

The communication reliability with quantum encryption is represented by:

$$P_s = 1 - e^{-\lambda \cdot K_{QKD}} \tag{2}$$

where

P_s is the probability of secure data transmission,

λ represents the channel quality, and

K_{QKD} is the quantum key length.

Table.1. Drone Sensor Deployment Parameters

Drone ID	Sensor Type	Altitude (m)	Coverage Area (km²)	Quantum Key Length (bits)
D1	Gas + Optical	50	0.8	1024
D2	Gas + Multispectral	60	1.0	1024
D3	Gas + Optical	45	0.7	1024

3.1 DATA ACQUISITION AND PREPROCESSING

Once the drones are deployed, sensor readings are collected continuously and preprocessed at the edge layer. Preprocessing involves noise reduction, normalization, and feature extraction to ensure the CNN model receives high-quality input data. Noise is filtered using adaptive Kalman filtering techniques, which dynamically adjust to temporal variations in sensor signals. The preprocessed data is then normalized using min-max scaling:

$$S'_{ij}(t) = \frac{S_{ij}(t) - S_{min}}{S_{max} - S_{min}} \tag{3}$$

Where $S'_{ij}(t)$ is the normalized reading, and S_{min}, S_{max} are the minimum and maximum values for sensor j.

The Feature extraction via Principal Component Analysis (PCA) is defined as:

$$Z = X \cdot W \tag{4}$$

where X is the preprocessed sensor data matrix, W is the eigenvector matrix of the covariance of X, and Z is the transformed feature vector.

The Adaptive Kalman filtering for time-series noise reduction:

$$\hat{x}_k = \hat{x}_{k-1} + K_k(y_k - H\hat{x}_{k-1}) \tag{5}$$

where $\hat{x}_k$ is the filtered estimate at time k, y_k is the sensor measurement, K_k is the Kalman gain, and H is the measurement matrix.

Table.2. Preprocessed Sensor Data Features

Drone ID	Sensor Type	CO_2 (ppm)	NO_2 (ppm)	PM2.5 (μg/m³)	Feature Vector (PCA)
D1	Gas + Optical	410	35	55	[0.71, -0.32, 0.59]
D2	Gas + Multispectral	420	38	48	[0.68, -0.29, 0.62]
D3	Gas + Optical	405	32	60	[0.72, -0.30, 0.57]

3.2 CNN-BASED POLLUTANT CLASSIFICATION

After preprocessing, the feature vectors are input to a CNN deployed at the edge for pollutant classification. The CNN comprises convolutional layers for spatial feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. The CNN is trained on labeled datasets to recognize pollutant types and concentration ranges.

The convolution operation for feature map extraction:

$$F_l^k = f\left(\sum_{m=1}^{M} W_l^{k,m} * X_{l-1}^m + b_l^k\right) \tag{6}$$

where F_l^k is the output of the k^{th} filter at layer l, X_{l-1}^m is the input feature map, $W_l^{k,m}$ is the filter weight, b_l^k is the bias, and $f(\cdot)$ is the activation function.

The softmax-based classification output:

$$P(y = c | X) = \frac{e^{z_c}}{\sum_{j=1}^{C} e^{z_j}} \tag{7}$$

where $P(y = c| X)$ is the probability of class c given input X, z_c is the class score, and C is the total number of classes.

Table.3. CNN Classification Output

Drone ID	Feature Vector	Predicted Pollutant	Concentration (ppm/μg/m³)	Confidence (%)
D1	[0.71, -0.32, 0.59]	CO_2	410	92
D2	[0.68, -0.29, 0.62]	NO_2	38	88
D3	[0.72, -0.30, 0.57]	PM2.5	60	90

3.3 EDGE AI INFERENCE AND DECISION MAKING

Edge computing enables real-time processing of drone-collected data without relying on cloud infrastructure. The edge layer executes the CNN model, aggregates results from multiple drones, and applies decision logic to detect hotspots and recommend corrective actions. Edge AI also dynamically adapts the drones' flight paths based on detected pollutant concentrations, ensuring targeted monitoring. The edge-level aggregation of predictions:

$$C_a = \frac{1}{N}\sum_{i=1}^{N} w_i \cdot C_i \tag{8}$$

where C_a is the combined concentration estimate, C_i is the local prediction from drone i, w_i is a reliability weight, and N is the number of drones. The flight path adjustment optimization using gradient-based

$$\vec{p}_{t+1} = \vec{p}_t - \eta \cdot \nabla_{\vec{p}} L(C_a, C_t) \tag{9}$$

where $\vec{p}_{t+1}$ is the updated position vector, η is the learning rate, and $L(\cdot)$ is the loss between predicted and target concentrations.

Table.4. Edge AI Aggregated Results

Drone Cluster	Aggregated Pollutant	Avg. Con.	Hotspot Detected	Action
1	CO_2	415	Yes	Increase monitoring
2	NO_2	37	No	Maintain path
3	PM2.5	58	Yes	Deploy mitigation drone

4. QUANTUM-SECURE COMMUNICATION

QKD ensures secure data transmission among drones and from drones to the base station. Each drone exchanges encryption keys using quantum entanglement, preventing eavesdropping and tampering. This step guarantees data integrity, especially for high-resolution sensor data critical for accurate pollution detection. The quantum-secured channel capacity:

$$C_q = \log_2(1 + \text{SNR}) \cdot (1 - P_e) \tag{10}$$

where C_q is the channel capacity, SNR is the signal-to-noise ratio, and P_e is the probability of eavesdropping detection.

The QKD key generation rate:

$$R_k = f_{\text{rep}} \cdot Q \cdot [1 - H(e)] \tag{11}$$

where R_k is the secure key rate, f_{rep} is the pulse repetition frequency, Q is the detection probability, $H(e)$ is the binary entropy function, and e is the quantum bit error rate (QBER).

Table.5. Quantum Communication Metrics

Drone ID	Channel SNR	Key Length (bits)	QBER (%)	Secure Data Rate (kbps)
D1	18 dB	1024	2.1	512
D2	20 dB	1024	1.8	540
D3	17 dB	1024	2.3	498

5. RESULTS AND DISCUSSION

The proposed Quantum Drone Sensor Network (Q-DSN) was evaluated using a combination of simulation and field-level experiments. The simulations were conducted using MATLAB R2025b and NS-3 network simulator to model drone mobility, sensor data acquisition, and communication behavior. The MATLAB environment facilitated the development and testing of the CNN-based pollutant classification model, while NS-3 was employed to simulate quantum-secure communication protocols and edge-based data aggregation.

The field experiments involved three custom-built drones, each equipped with multi-gas sensors, multispectral cameras, and embedded NVIDIA Jetson Nano boards for onboard edge AI inference. These drones operated in a controlled urban testbed environment of approximately 2 km², capturing real-time pollutant data under varying environmental conditions.

Computational resources for simulation included a workstation with Intel Core i9-13900K CPU, 64 GB RAM, and NVIDIA RTX 4090 GPU, which was used for both CNN training and large-scale simulation of drone deployments. The Jetson Nano boards onboard drones performed edge-level inference with minimal latency, which shows the feasibility of real-time processing in practical scenarios. Data collected from field experiments were logged for post-processing and validation against simulation results.

Table.6. Experimental Setup and Parameters

Parameter	Value / Setting
Number of drones	3
Drone altitude	45–60 m
Drone speed	5–12 m/s
Gas sensors	CO_2, NO_2, PM2.5, VOCs
Sampling rate	1 Hz
Edge processor	NVIDIA Jetson Nano
CNN input size	32 × 32 × 3
Quantum key length	1024 bits
Communication protocol	Quantum-secure & Wi-Fi 6
Testbed area	2 km²

5.1 PERFORMANCE METRICS

The proposed framework was evaluated using the metrics, which quantify detection accuracy, latency, energy efficiency, communication reliability, and system scalability.

- **Detection Accuracy (DA):** Detection accuracy measures the percentage of correctly classified pollutants by the CNN model. It was computed as:

$$DA = \frac{N_{\text{correct}}}{N_{\text{total}}} \times 100 \tag{12}$$

where $N_{correct}$ is the number of correct predictions, and N_{total} is the total number of predictions. Both simulation and field experiments showed an improvement of approximately 37% over baseline IoT-based methods.

- **Latency (L):** Latency represents the total time between sensor data acquisition and pollutant classification at the edge. Lower latency ensures timely environmental monitoring. It was measured as:

$$L = t_{in} + t_{tr} \tag{13}$$

The proposed edge-based architecture reduced latency by 42% compared to cloud-dependent models.

- **Energy Efficiency (EE):** Energy efficiency reflects the ratio of computational tasks completed to the total energy consumed by the drones. It was defined as:

$$EE = \frac{\text{Operations completed}}{\text{Total energy consumed (J)}} \tag{14}$$

The use of edge AI inference allowed energy savings of **35%**, extending drone operational time.

- **Communication Reliability (CR):** Communication reliability quantifies successful data transmissions without loss or interference, especially under quantum-secured channels. It was calculated as:

$$CR = \frac{N_s}{N_{tx}} \times 100 \tag{15}$$

- **System Scalability (SS):** System scalability measures the framework's ability to maintain performance when the number of drones or sensing nodes increases. Performance trends were analyzed using:

$$SS = \frac{\text{Performance metric with } N_{\text{drones}}}{\text{Performance metric with baseline drones}} \tag{16}$$

5.2 COMPARISON WITH STATIC IOT SENSOR NETWORK

Table.7. Performance of Static IoT Sensor Network vs Proposed Q-DSN

Area Covered (km²)	Method	DA (%)	L (s)	EE (Ops/J)	CR (%)	SI
0.5	Static IoT	62	4.5	0.85	88	0.7
	Proposed	84	2.1	1.15	95	1.0

1.0	Static IoT	60	5.0	0.82	85	0.68
	Proposed	83	2.3	1.12	94	1.0
1.5	Static IoT	58	5.5	0.80	83	0.65
	Proposed	82	2.5	1.10	93	1.0
2.0	Static IoT	55	6.0	0.78	80	0.63
	Proposed	81	2.7	1.08	92	1.0

5.3 COMPARISON WITH DRONE-BASED AIR QUALITY MONITORING

Table.8. Performance of Drone-Based Monitoring vs Proposed Q-DSN

Area Covered (km²)	Method	DA (%)	L (s)	EE (Ops/J)	CR (%)	SI
0.5	Drone-Based	70	3.8	0.92	90	0.8
	Proposed	84	2.1	1.15	95	1.0
1.0	Drone-Based	68	4.2	0.89	88	0.78
	Proposed	83	2.3	1.12	94	1.0
1.5	Drone-Based	65	4.8	0.85	85	0.75
	Proposed	82	2.5	1.10	93	1.0
2.0	Drone-Based	62	5.2	0.82	83	0.72
	Proposed	81	2.7	1.08	92	1.0

5.4 COMPARISON WITH EDGE-ASSISTED POLLUTION DETECTION

Table.9. Performance of Edge-Assisted Detection vs Proposed Q-DSN

Area Covered (km²)	Method	DA (%)	L (s)	EE (Ops/J)	CR (%)	SI
0.5	Edge-Assisted	75	2.9	1.05	91	0.85
	Proposed	84	2.1	1.15	95	1.0
1.0	Edge-Assisted	73	3.2	1.02	90	0.82
	Proposed	83	2.3	1.12	94	1.0
1.5	Edge-Assisted	70	3.6	0.98	88	0.80
	Proposed	82	2.5	1.10	93	1.0
2.0	Edge-Assisted	68	4.0	0.95	86	0.78
	Proposed	81	2.7	1.08	92	1.0

From Table.7–Table.9, it is evident that the proposed Q-DSN consistently outperforms all existing methods across the 2 km² testbed. Detection accuracy remains above 81%, compared to 55–75% for baseline methods. Latency is reduced significantly, from 2.9–6.0 s to 2.1–2.7 s, which shows the advantage of edge AI inference. Energy efficiency improves by approximately 20–35%, and communication reliability exceeds 92% due to quantum-secured channels. The scalability index remains constant at 1.0 for Q-DSN, highlighting its ability to maintain performance when the monitoring area expands, unlike traditional methods whose metrics degrade progressively with area increase.

5.5 COMPARISON WITH STATIC IOT SENSOR NETWORK

Table.10. Performance of Static IoT Sensor Network vs Proposed Q-DSN under Varying Key Lengths

Key Length (bits)	Method	DA (%)	L (s)	EE (Ops/J)	CR (%)	SI
256	Static IoT	58	5.8	0.78	82	0.62
	Proposed	80	2.5	1.10	92	1.0
512	Static IoT	56	6.0	0.76	80	0.60
	Proposed	81	2.6	1.09	92	1.0
768	Static IoT	55	6.2	0.74	78	0.58
	Proposed	82	2.6	1.08	92	1.0
1024	Static IoT	55	6.3	0.73	77	0.57
	Proposed	83	2.7	1.08	92	1.0

5.6 COMPARISON WITH DRONE-BASED AIR QUALITY MONITORING

Table.11. Performance of Drone-Based Monitoring vs Proposed Q-DSN under Varying Key Lengths (Table 11)

Key Length (bits)	Method	DA (%)	L (s)	EE (Ops/J)	CR (%)	SI
256	Drone-Based	64	5.0	0.84	86	0.72
	Proposed	80	2.5	1.10	92	1.0
512	Drone-Based	63	5.2	0.82	85	0.70
	Proposed	81	2.6	1.09	92	1.0
768	Drone-Based	62	5.4	0.80	84	0.68
	Proposed	82	2.6	1.08	92	1.0
1024	Drone-Based	61	5.6	0.78	83	0.67
	Proposed	83	2.7	1.08	92	1.0

5.7 COMPARISON WITH EDGE-ASSISTED POLLUTION DETECTION

Table.12. Performance of Edge-Assisted Detection vs Proposed Q-DSN under Varying Key Lengths

Key Length (bits)	Method	DA (%)	L (s)	EE (Ops/J)	CR (%)	SI
256	Edge-Assisted	72	3.5	1.00	89	0.82
	Proposed	80	2.5	1.10	92	1.0
512	Edge-Assisted	71	3.7	0.98	88	0.80
	Proposed	81	2.6	1.09	92	1.0
768	Edge-Assisted	70	3.9	0.96	87	0.78
	Proposed	82	2.6	1.08	92	1.0
1024	Edge-Assisted	68	4.0	0.95	86	0.77
	Proposed	83	2.7	1.08	92	1.0

From Table.10–Table.12, the proposed Q-DSN consistently outperforms all existing methods across different quantum key lengths. Detection accuracy improved by 8–28% compared to existing methods, remaining above 80% even at 1024 bits.

Latency decreased from 3.5–6.3 s to 2.5–2.7 s due to edge AI processing, while energy efficiency improved by 10–35%, reflecting optimized computation at drones. Communication reliability stabilized at 92% because of quantum-secured channels, whereas baseline methods degraded as key length increased. The scalability index of 1.0 confirms the Q-DSN maintains robust performance under secure communication constraints, unlike traditional approaches whose metrics decline progressively.

6. CONCLUSION

This study presents a Q-DSN with CNNs and Edge AI for intelligent urban pollution detection. The proposed framework effectively combines multi-sensor drone deployments, edge-level processing, and quantum-secured communication to address the limitations of existing IoT- and drone-based monitoring systems. Simulation and field experiments over a 2 km^2 urban testbed demonstrated that Q-DSN consistently outperformed baseline methods in all critical performance metrics. Detection accuracy remained above 81%, representing an improvement of up to 28% over traditional static IoT sensors, drone-only monitoring, and edge-assisted frameworks. Latency was significantly reduced to 2.1–2.7 seconds, enabling real-time pollutant detection, while energy efficiency improved by 20–35%, extending drone operational time. Communication reliability stabilized at 92%, benefiting from quantum key distribution, and the system maintained robust scalability even as area coverage and quantum key lengths increased. The combination of CNN-based feature extraction with edge inference allowed accurate classification of CO_2, NO_2, PM2.5, and VOCs under dynamic environmental conditions.

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